SEMARAK ILMU PUBLISHING

Journal of Advanced Research in Applied Sciences and Engineering Technology

Journal homepage: https://semarakilmu.com.my/journals/index.php/applied_sciences_eng_tech/index
ISSN: 2462-1943

Accurate Range Free Location based Partial Derivative and Stochastic Feedforward Neural Network Hyperbolic-based Agriculture Sensor Network Formation

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ARTICLE INFO

Article history:
Received 6 April 2023
Received in revised form 27 June 2023
Accepted 20 August 2023
Available online 8 September 2023

Keywords:
Wireless Sensor Networks; Irrigation Management System; Game Theory; Partial Derivative Regression; Laurent Approximation; Stochastic Feedforward; Hyperbolic

ABSTRACT

Wireless sensor networks (WSN) authorize the control of different source environmental aspects and crop states as far as precision agriculture is concerned. Nevertheless, the complicated agricultural environment brings about the WSN topology changing often and hence link association likelihood is laborious to predict. Information pertaining to agriculture is an essential distress for localization-based service in the domain of WSNs. Smooth planning and control as the most typical range-free localization method localization performance is said to be good in even distributed networks. Nevertheless, it demonstrated extremely poor accuracy under that in an urgent issue that required to be addressed. In this work a novel topology construction method called, Partial Derivative Laurent Approximation and Stochastic Feedforward Hyperbolic (PDLA-SFH) based Agriculture Sensor Network Formation is proposed. The proposed method is split into three steps. They are agriculture sensor topology construction, average hop size distance validation and position estimation. First topology construction is performed by employing Game Theory Partial Derivative Regression Coefficient-based Topology model. Second, Laurent Approximation-based Hop Size Distance validation model is designed for optimal topology formation. Finally, the Stochastic Feedforward Hyperbolic-based Position Estimation is modeled. The simulation results performed in NS3 showed that the proposed localization algorithms can attain better localization performance in terms of accuracy, time and error rate in comparison with other existing methods such as basic Digital Twins and Autonomous Groups Particles Swarm Optimization (AGPSO) under distinct arbitrary network topologies.

1. Introduction

In precision agriculture (PA), several factors like, type of the soil and temperature differs in an automatic fashion depending on the region. Nevertheless, any irrigation system must be pliable in adapting to differing variations. Irrigation management based on the Wireless Sensor Networks (WSNs) however can adapt to any type of scheduling technique to meet particular environmental

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https://doi.org/10.37934/araset.32.2.6078

requirements. But WSNs being under evolution stage are at times found to be unreliable, and hence easily lose communication particularly when deployed in harsh environment like an agricultural field.

A method called, Digital Twins was designed with the purpose of combining smart farming towards improvement in terms of both farming productivity and sustainability [1]. The Digital Twin was designed on the behaviour and states aspects over its lifetime for farm management, therefore ensuring smooth planning and control. With this type of design, farmers in turn were found to manage operations in a remote manner upon comparison with the traditional mechanisms that hugely depended on direct observation manually. As a result, deviations were found to be immediately addressed based on real-life data and therefore ensured advance smart farming in an accurate and precise manner. However, location information is said to be the major concerns as far as localization-based service is concerned in the domain wireless sensor networks (WSNs). Nevertheless, Digital Twins demonstrated exceedingly poor accuracy under anisotropic networks that remains a major cause to be addressed. With this objective an optimized distance vector-based hop localization employing, Autonomous Groups Particles Swarm Optimization (AGPSO) was proposed by Fengrong *et al.*, [2] for optimizing coordinate initially was designed. Moreover, localization coverage was also determined employing evaluation indicator. With this type of design resulted in the improvement of localization accuracy and computational complexity.

As far as the agriculture domain is considered Artificial Intelligence is considered as the upcoming technology. As a result the AI-based machines, has taken hold of the present agriculture system to a distinct extent. This AI-based technology has improved the production of crop and enhanced monitoring in a real time manner. Moreover, the state-of-the-art technologies utilizing agricultural drones have made an extensive contribution.

According to Dzaky and Sang-Hwa, [3] network formation using Q-learning was designed based on minimal cell and transmission queue conditions. Application of AI during the design stage for optimized irrigation process was designed [4]. Yet another particle swarm optimization technique was applied in with the purpose of improving the lifetime of design of network in agriculture domain [5].

The evolution of WSNs stimulated a new regulation of research in agricultural and farming domain. Over the past few years, WSNs are extensively appertained in several agricultural applications. According to Ojha *et al.*, [6] the prospective of WSN applications were reviewed, and the particular concerns and confronts analogous with arranging WSNs for enhanced farming was investigated in detail. Also to concentrate on the individual requirements, the sensors and communication strategies related with WSNs in agricultural field of interest were also inspected in an exhaustive manner.

Scheduling of corresponding sensor activity is analytical for extending the WSN lifetime. However, most prevailing methods were designed with the assumption of positioning the sensors in a predetermined sensing range. To address on this aspect, Neighborhood based Estimation of Distribution Algorithm was designed [7]. With this type of design, the network lifetime was said to be improved significantly. Yet another quantum based swarm optimization algorithm was presented by Velasquez *et al.*, [8] that with the aid of approximate separation distance ensured robustness with improved network lifetime.

Nevertheless, a design of intelligent and robust sensor network formation for agriculture farm land in wireless network still remains major concern to be addressed. Therefore, our goal is to develop the right learning mechanism that can achieve acceptable network formation accuracy, the successful agriculture farmland design in a representative track, but which operates in real-time within time and minimal complexity of its target automotive platform. In order to achieve this, the mechanism we took was to split the overall process into topology construction, distance validation and position estimation that can be used for agriculture sensor network formation. The extensive plan to associate a suitable model is to initially, design agricultural WSN model with which the point of interest of sensor samples can be obtained in a precise manner according to distinct volumetric water readings and temperature readings.

1.1 Contributing Remarks

In summary, the contributions of the method proposed in this paper are:

- We modified the conventional game theory by employing Game Theory Partial Derivative Regression Coefficient-based Topology construction and used both the transmission power and residual energy aspects into consideration for obtaining optimal topology formation.
- We proposed a novel Laurent Singularity-based Hop Size Distance validation model, despite having a light architecture in comparison with Digital Twins and AGPSO, is able to successfully perform smooth and robust sensor network formation for agriculture land.
- To present Stochastic Feedforward Hyperbolic-based Position Estimation employing both distance and position estimates between anchor sensor node and regular sensing node for obtaining intelligent positioning.
- We have demonstrated the suitability of a new proposed Partial Derivative Laurent Approximation and Stochastic Feedforward Hyperbolic (PDLA-SFH) based Agriculture Sensor Network Formation by doing the performance evaluation in simulated environment, where the PDLA-SFH method shows the best performance in terms of network formation time, network formation error rate, network formation complexity and network formation accuracy among three implemented solutions.

1.2 Organization of the Work

In the next section, the related work is presented. In section 2 the reviews of the state-of-the-art methods and conventional methods for network formation is briefed. The overall structure and implementation details of the proposed PDLA-SFH method are also given in this section. Results and discussion of the implementation of all three methods and inference during sensor network formation for farmland are given in section 4. The conclusion remarks is given in the last section 5.

2. Related works

With the evolution of the Internet of Things (IoT), WSNs are extensively researched and transposed our life significantly. Nevertheless, as far as precision agriculture is concerned, WSNs have played a significant role. However, with the application of mobile autonomous vehicles carrying multi-sensors being applied in precision agriculture, the sensor nodes connectivity changes in an arbitrary fashion. As a result, the stability and reliability of sensor network communication has to be enhanced significantly.

A novel method based on an Open vSwitch extension that can improve agriculture network survivability and stability was presented by Huang *et al*., [9]. A survey of machine learning in precision agriculture was investigated by Condran *et al*., [10]. A systematic review of machine learning in the field of agriculture was proposed [11]. In the face of the perception similarity may have interested agricultural practices however in the recent past few years, the persistence of agricultural science is found to be accurate, precise and robust than ever. The consequence of the techniques based on IoT has improved smart agriculture or precision agriculture. The power and potentiality of computing mechanisms, like, Iot, WSNs and machine learning in agriculture was reviewed by Akhter *et al*., [12]. A detailed bibliographic analysis on application of machine learning for smart agriculture was presented by Ünal and Zeynep, [13].

The formation of state-of-the-art technological solutions in agricultural sector directs in accomplishing the development objectives in a sustainable fashion. As a result, the organization involving the structure formation for Food and Agriculture and the International Funding performed for the development of Agricultural sector made an appearance in boosting exploration, interest and rationality in agriculture.

A spatio temporal semantic design was presented by San *et al*., [14] for improved interoperability. Yet another precise agriculture mechanism focusing on the root mean square error was designed by Dhanavanthan *et al*., [15]. Also as the modern farmers are at the central of the social network, information obtained are also said to be supervised and managed within the community in an accurate fashion.

Aspects of social network involved in the design of smart agriculture were presented by Albizua *et al*., [16]. Yet another social network analysis model for knowledge exchange concerning topology construction was presented by Wood *et al*., [17]. An exponential random graph modeling based on the social network analysis was presented by Hermans *et al*., [18] with the purpose of investigating the structural aspects involved in agriculture network formation. A holistic review on the application of artificial intelligence in smart farming and precise agriculture was proposed by Elbasi *et al*., [19]. Cloud based application for precise agriculture employing AI was presented by Ampatzidis *et al*., [20].

A low-cost wireless sensor network for drip irrigation monitoring designed by Vandôme *et al*., [21] . A Mobile Ad-hoc sensor node was introduced by Li *et al*., [22] to comprise the sensors to collect real time environment from the agricultural land with wireless communication technology and process the data before data sharing with other nodes in the network. Wireless sensor networks in ginseng field in precision agriculture were designed by Parashar *et al*., [23]. According to Abdollahi *et al*., [24], efficient soil resistivity measurement technique using wireless sensor network (WSN) has been proposed to collect and process the data for application in the agriculture fields.

3. Methodology

Owing to the complexity involved in agricultural environment with the crop growth being influenced by several factors, like, soil moisture, climatic conditions, it becomes laborious process for conventional wired monitoring system in precisely sensing the agricultural environments. WSN on the other hand consists of microsensors that possess the capability of low cost and high precision that makes high appropriateness for smart agriculture. Prevailing topology control mechanisms can though enhance the network performance to an indisputable degree, nevertheless in the field of agriculture, compactness nature of crops and composite climate provoke the multipath influence of wireless signals, therefore causing unsteady like associated probability.

3.1 Agricultural WSN Model

Let us consider that 'n' nodes sense the environment and are distributed in an even fashion in the farm, represented by a graph '$G(V, E, P)$', where '$V = \{1,2,..,n\}$' denotes the nodes set in the agricultural WSN and '$E = \{e_{ij}, i \in V, j \in V, i \neq j\}$' denotes the association between nodes. Therefore 'e_{ij}' is set to '1', upon communication between nodes and on contrary 'e_{ij}' is set to '0'. Finally, '$P = \{(P_1, P_2, \ldots, P_n), P_i \in [P_{Min}, P_{Max}]\}$' denotes the transmission power of all sensing nodes in process with unique identifier (i.e., ID). In this work the proposed Partial Derivative Laurent

Approximation and Stochastic Feedforward Hyperbolic-based Agriculture Sensor Network Formation method, the agricultural sensor network formation process is split into three sections, sensor nodes participating in the agricultural WSN model for network formation stream their positions by employing Game Theory Partial Derivative Regression Coefficient, a novel formulates for average hop size distance is introduced by employing Laurent Approximation-based Hop Size Distance validation model, and the Stochastic Feedforward Hyperbolic-based Position Estimation model is applied to measures the agriculture nodes location.

3.2 Game Theory Partial Derivative Regression Coefficient-based Topology model

The topology construction in our work initiates the process with the game theory formulation when applied to topology control obtains an optimal topology by taking into consideration the energy consumption of each node. The potential game in our agriculture WSN optimal topology construction including 'n' nodes, with partial derivative strategy 'S' is expressed as '$f = \{f_1, f_2, \dots, f_n\}$' where '$f_i$' represents the optimal price obtained by node 'i' with the policy (i.e., transmission power) set '$TP = \{TP_1, TP_2, \dots, TP_n\}$' respectively. Agricultural WSN topology or network formation in our work employing Game Theory Partial Derivative Regression Coefficient-based Topology model is optimized by taking into consideration multiple factors like, node magnitude, initial energy consumption, residual energy, and network lifetime. Figure 1 shows the structure of Game Theory Partial Derivative Regression Coefficient-based Topology model.

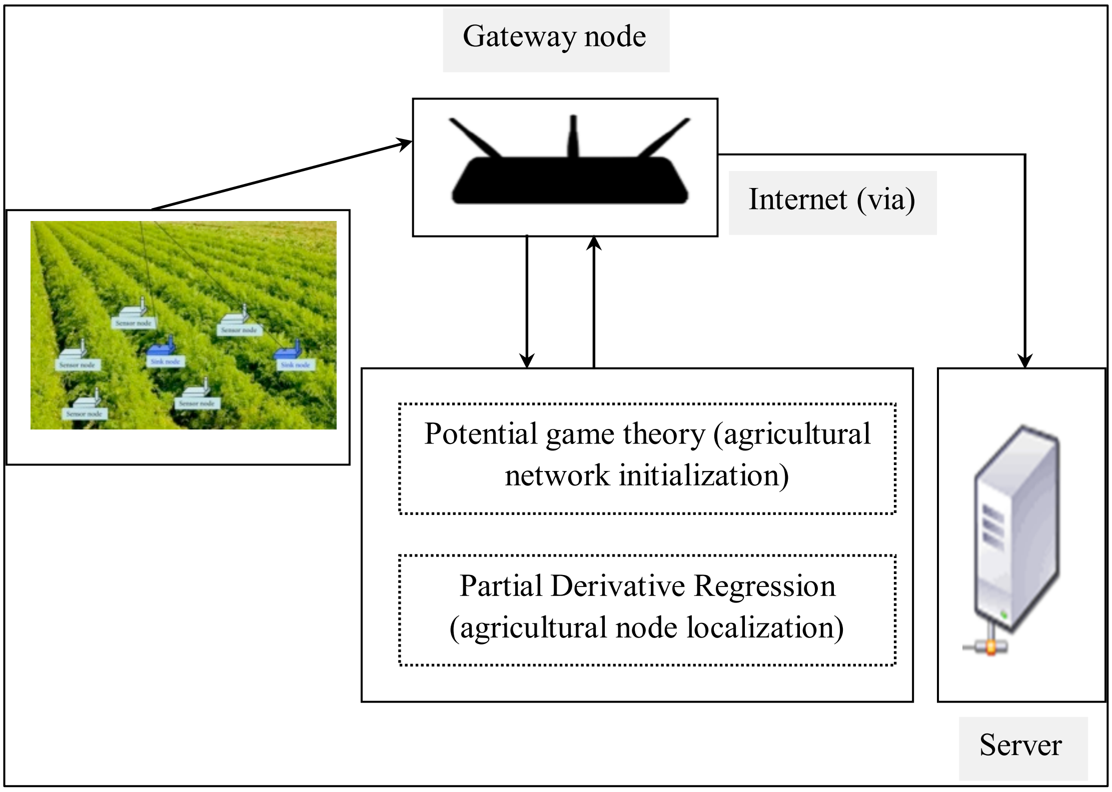

Fig. 1. Structure of Game Theory Partial Derivative Regression Coefficient-based Topology model

As shown in the above figure, in the initial stage, each sensor node 'n_i' from the agricultural WSN network floods the hello packet along with the location possessing initial energy, node magnitude via potential game theory. The potential game theory for agricultural network initialization is mathematically represented as given below.

$$f(TP_i, TP_j) = f(TP_i, TP_j)\left(w_i TP_i^{max}\frac{NL_i^{max}}{NL_i^{min}} + w_j\frac{Mag(TP_i)}{NN_i^{max}} + \frac{RE_i^{min}}{RE^{max}}\right) - w_i TP_i\frac{NL_i^{max}}{NL_i^{min}} - w_j\frac{Mag(TP_i)}{NN_i^{max}};\ RE_i > RE_{Thr} \quad (1)$$

$$f(TP_i, TP_j) = f(TP_i, TP_j)\left(w_i TP_i^{max}\frac{NL_i^{max}}{NL_i^{min}}\right) - w_i TP_i\frac{NL_i^{max}}{NL_i^{min}}; RE_i < RE_{Thr} \quad (2)$$

From the above equations (1) and (2), 'TP_i' and 'TP_j' represents the transmission power of node 'i' and 'j' respectively. In addition '$f(TP_i, TP_j)$' represents the connectivity between nodes with '$f(TP_i, TP_j) = 1$' representing the agriculture WSN is connected and in contrary '$f(TP_i, TP_j) = 0$' representing the agriculture WSN is not connected via weights 'w_i' and 'w_j'. Moreover, 'NL_i^{max}', 'NL_i^{min}', '$Mag(TP_i)$', 'NN_i^{max}', 'RE_i^{min}' and 'RE^{max}' represents the maximum network lifetime, minimum network lifetime, magnitude of node 'i', neighbor nodes with maximum transmission power, minimum residual energy and maximal residual energy. 'RE_i' and 'RE_{Thr}' represents the residual energy of node 'i' and residual energy threshold to validate the network formation. Following which the Partial Derivative Regression for modeling sensor nodes localization is mathematically formulated as given below.

$$PDR_t = \frac{\partial f(TP_i, TP_j)}{\partial TP_i}\alpha_t + \mu_t, t = 1,2, \dots, T \quad (3)$$

From the above equation (3), 'T' represents the sample length of agricultural WSN network, with '$f(TP_i, TP_j)_t$' denoting the '$i * j$' dimensional assessment matrix based on the transmission power, 'α_t' representing the '$j * 1$' state vector and 'y_t' denoting the '$i * 1$' observable vector respectively. Moreover, if '$\alpha_t \geq 1$', then the agricultural WSN network is said to be flooded with the corresponding node location and on contrary if '$\alpha_t < 1$', then there remains room for nodes to provide their corresponding node location. The pseudo code representation of Game Theory Partial Derivative Regression Coefficient-based Topology construction is given below.

Input: Nodes '$N = \{N_1, N_2, \dots, N_n\}$'
Output: Optimal topology formation 'Top'
Step 1: **Initialize** 'n', 'TP_i', 'TP_j', weights 'w_i', 'w_j' Step 2: **Initialize** residual energy of node 'i' 'RE_i', residual energy threshold 'RE_{Thr}' Step 3: **Begin** Step 4: **For** each Nodes 'N' Step 5: Formulate potential game theory for agricultural network formation as given in equations (1) and (2) Step 6: Formulate Partial Derivative Regression for obtaining the state vector as given in equation (3) Step 7: **If** '$\alpha_t \geq 1$' Step 8: **Then** agricultural WSN network is said to be flooded Step 9: **Else** Agricultural WSN network is not said to be flooded Step 10**: End if** Step 11: **End for** Step 12: **End**

Algorithm 1 Game Theory Partial Derivative Regression Coefficient-based Topology construction

As given in the above algorithm with the objective of constructing agricultural internet of things system for wireless sensor network for smart agriculture, the network formation time plays a major role. Earlier the network being deployed in farmland so that the time of node deployed reaches the minimum and the formed monitoring network can efficiently cover the entire farmland. With this objective, the agricultural network initialization is made by means of potential game theory focusing on the transmission power. Second, a Partial Derivative Regression model is formulated with the initialized agricultural network so that agricultural node localization is achieved with minimum time. In our work a star topology is formed where the agricultural sensor nodes are connected to directly a hub or sink node.

3.3 Laurent Approximation-based Hop Size Distance validation model

It is known that the localization error generated optimized localization algorithm is due to the uncertainty involved that it is said to be occurred while evaluating the distance in terms of average hop size and minimum hop count. A tradeoff is said to occur during this duo estimation (i.e., hop size and hop count). As a result the error generated is relatively large and it therefore influences the localization accuracy of sensor nodes extensively. In our work, Laurent Singularity-based Hop Size Distance validation model is employed as they are able to identify the best solution. Figure 2 shows the structure of Laurent Singularity-based Hop Size Distance validation model.

As shown in figure 2, with the agricultural topology formatted network in hand, the objective remains in designing Hop Size Distance validation based on Laurent Singularity function. Let 'ϵ_{ik}' represent the approximation error of distance between '$i-th$' regular sensing node and '$k-th$' anchor sensed node then the approximation error is mathematically stated as given below.

$$\epsilon_{ik} = Dis'_{ik} - Dis_{ik} \tag{4}$$

From the above equation (4) employing estimated distance and actual distance between '$i-th$' regular sensing node and '$k-th$' anchor sensed node. According to the above topology construction we have,

$$Pos_{ik} = \begin{cases} p_i = p'_i + \delta p_i \\ q_i = q'_i + \delta q_i \end{cases} \tag{5}$$

Form the above equation (5), 'δp_i' and 'δq_i' represents the position errors to be determined for each sample instances. Then, by employing the Laurent series, approximation function is formulated for estimating hop size distance as given below.

$$AvgHopSize = Dis_{ik} = Dis''_{ik} + \beta k_1 \delta p_i + \beta k_2 \delta q_i \tag{6}$$

$$Dis''_{ik} = \sqrt{(p'_i - x_k)^2 - (q'_i - y_k)^2} \tag{7}$$

$$\beta k_1 = \frac{\partial Dis_{ik}}{\partial p} = \frac{p'_i - x_k}{Dis''_{ik}} \tag{8}$$

$$\beta k_2 = \frac{\partial Dis_{ik}}{\partial q} = \frac{q'_i - y_k}{Dis''_{ik}} \tag{9}$$

From the above equations (6), (7), (8) and (9), hop size distance is obtained with minimal error for agriculture sensor network formation.

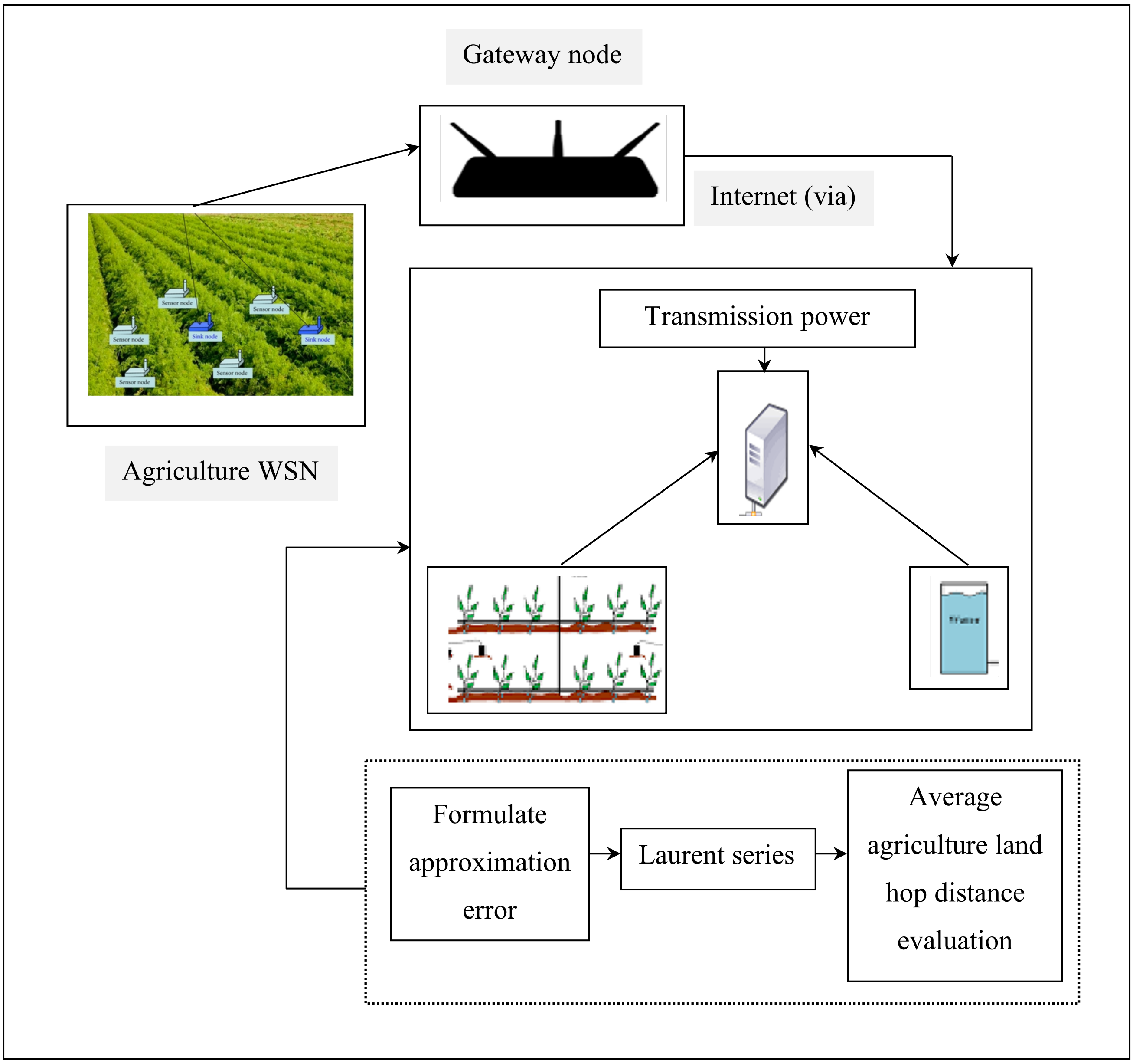

Fig. 2. Structure of Laurent Singularity-based Hop Size Distance validation model

The pseudo code representation of Laurent Approximation-based Hop Size Distance validation is given in algorithm 2.

As can be seen the algorithm, with the objective of minimizing the node formation error with maximum convergence speed, two different errors based on the approximation error and position error with respect to regular sensor node and anchor sensed nodes are initially obtained. Second, based on the resultant error values, hop distance is measured employing approximation function. This in turn ensures agricultural sensor network formation with minimal error by taking into consideration both the approximation error and position error.

Input: Nodes '$N = \{N_1, N_2, \dots, N_n\}$'
Output: Minimal error-based average hop size distance
Step 1: **Initialize** topology formed 'Top' Step 2: **Begin** Step 3: **For** each '$i - th$' regular sensing node, '$k - th$' anchor sensed node and topology formed Step 4: Formulate approximation error as given in equation (4) Step 5: Evaluate position errors as given in equation (5)' Step 6: **If** '$\epsilon_{ik} > Pos_{ik}$' Step 7: Error in distance validation Step 8: **Go to** step 4 Step 9: **End if** Step 10: **If** '$\epsilon_{ik} \leq Pos_{ik}$' Step 11: Evaluate hop size distance via approximation function as given in equations (6), (7), (8) and (9) Step 12: Return average hop size '$AvgHopSize$' Step 13: **End if** Step 14: **End for** Step 15: **End**

Algorithm 2 Laurent Approximation-based Hop Size Distance validation

3.4 Stochastic Feedforward Hyperbolic-based Position Estimation model

Finally in this section with the constructed topology and minimal error-based hop size distance evolved, position estimation for agriculture sensor network formation is modeled by employing Stochastic Feedforward Hyperbolic-based Position Estimation model. The Stochastic Feedforward Hyperbolic-based Position Estimation model involves factorization of joint distribution and an adaptive filter designing for designing computationally efficient network formation. Figure 3 illustrates the Stochastic Feedforward Hyperbolic-based Position Estimation model.

As shown in figure 3, in the position estimation learning model the iterative procedure starts from the formed topology, flows through average hop size, and then generates output or the actual position estimation. The Stochastic Feedforward network is initially formulated as given below.

$$Prob(Pos, AvgHopSize, Top) = Prob(Pos|AvgHopSize)\, Prob(AvgHopSize|Top) \quad (10)$$

Based on the above equation results (10), a Stochastic Feedforward network is initially modeled. Second with the modeled network, a hyperbolic location analysis is applied. Let us assume that 'x_i' represents the coordinate of anchor sensed node 'i' and 'x_n' represents the coordinate of regular sensing node 'n', then the distance estimated is mathematically represented as given below.

$$Dis_{i,n}^2 = AvgHopSize[(x_i - x_n)^2 + (y_i - y_n)^2] \quad (11)$$

Let us further assume that '$U_i = (x_i^2 + y_i^2)$' and '$V_i = (x_n^2 + y_n^2)$', then the estimated position of 'n' is mathematically represented as given below.

$$Pos_{i,n}^2 - U^2 = AvgHopSize[-2x_i x_k - 2y_i y_k + V_i] \quad (12)$$

Based on the above formulation, the matrix representation is provided as given below.

$$ARes = AvgHopSize\,[b] \tag{13}$$

$$A = \begin{bmatrix} -2x_1 & -2y_1 & 1 \\ -2x_2 & -2y_2 & 1 \\ \dots & \dots & \dots \\ -2x_n & -2y_n & 1 \end{bmatrix}; Res = [x_n, y_n, V_n]; b = \begin{bmatrix} Pos_{1,n}^2 & -U_1 \\ Pos_{2,n}^2 & -U_2 \\ \dots & \dots \\ Pos_{k,n}^2 & -U_k \end{bmatrix} \tag{14}$$

According to equation as given above (14), using the adaptive filter, the result 'Res' is obtained as given below.

$$Res = (A^T A)^{-1} A^T\ AvgHopSize\,[b] \tag{15}$$

With the above obtained intermediate results, the point estimation of each sensor's are evolved as given below.

$$x_n = Res(1);\ y_n = Res(2) \tag{16}$$

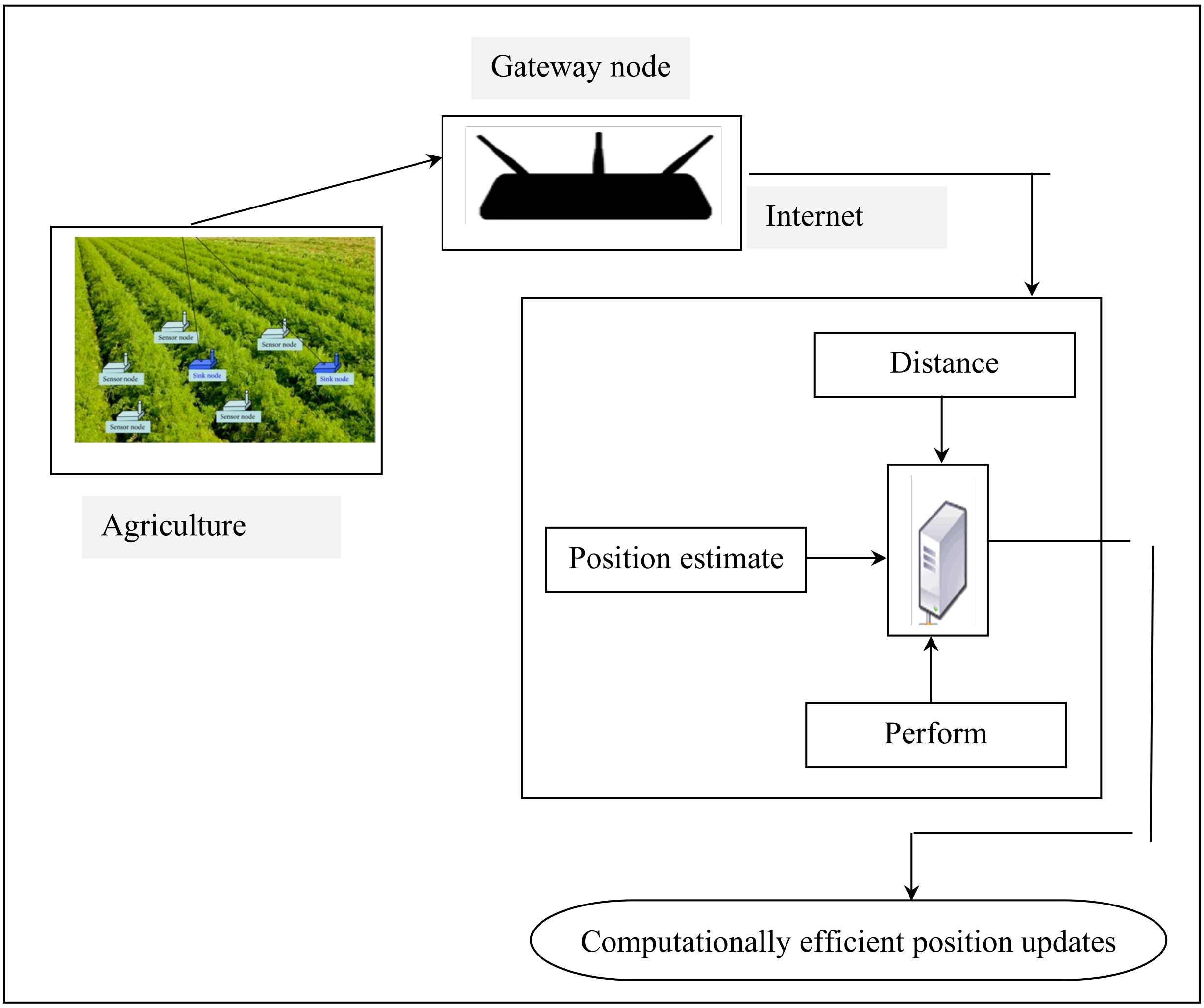

Fig. 3. Structure of Stochastic Feedforward Hyperbolic-based Position Estimation model

Finally, by allowing for both distance and average hop size in a single Stochastic Feedforward network hidden layer, allowing the mean '$Prob(Pos, AvgHopSize, Top)$' to have contributions from two elements, one from the hidden state 'H_i' (i.e., application of hyperbolic location analysis), and another one from defining a mapping between nodes 'x_n, y_n', computationally efficient network formation are guaranteed. The pseudo code description of Stochastic Feedforward Hyperbolic-based Position Estimation for location identification is given below.

Input: Nodes '$N = \{N_1, N_2, \dots, N_n\}$'
Output: computationally efficient node location identification
Step 1: **Initialize** topology formed, average hop size '$AvgHopSize$' Step 2: **Begin** Step 3: **For** each '$i-th$' regular sensing node, '$k-th$' anchor sensed node, topology formed and average hop size '$AvgHopSize$' Step 4: Formulate Stochastic Feedforward network as given in equation (10) Step 5: Evaluate distance estimates as given in equation (11) Step 6: Evaluate position estimates as given in equation (12) Step 7: Formulate matrix representation as given in equations (13) and (14) Step 8: Evaluate agriculture nodes location of corresponding coordinate as given in equations (15) and (16) Step 9: **End for** Step 10: **End**

Algorithm 3 Stochastic Feedforward Hyperbolic-based Position Estimation

As given in the above algorithm with the objective of evolving computationally efficient position updates two distinct principles are modeled. First, Stochastic Feedforward network is designed in the first input layer. Seconds, both distance and position estimates between anchor sensor node and regular sensing node are formulated using distance estimation. Finally, with the aid of matrix representation, the location information of agriculture nodes is arrived at in a computationally efficient manner.

4. Experimental setup

The proposed Partial Derivative Laurent Approximation and Stochastic Feedforward Hyperbolic (PDLA-SFH) based Agriculture Sensor Network Formation is compared with Digital Twins [1] and Autonomous Groups Particles Swarm Optimization (AGPSO) [2] that we re-implemented in order to conduct an objective performance evaluation of novel design. The state-of-the-art methods with the PDLA-SFH were implemented, trained with the same Cook Farm sensor network data set (i.e., https://data.nal.usda.gov/dataset/data-field-scale-sensor-network-data-set-monitoring-and-modeling-spatial-and-temporal-variation-soil-moisture-dryland_agricultural-field) were utilized for inference in simulator for sensor network formation. The data has been found in the Cook Farm sensor network dataset; the cook farm data set contains four data frames. The readings data frame contains measurements of volumetric water content (cubic-m/cubic-m), temperature (degree C) and bulk electrical conductivity (dS/m), measured at 42 locations using 5TE sensors at five standard depths (0.3, 0.6, 0.9, 1.2, 1.5 m) for the period. The results were compared in terms of performance metrics like, network formation time, network formation complexity, network formation accuracy and network formation error rate. The experimental data processing is simulated via NS3. For performing fair comparison same cook farm sensor network dataset was applied for all the three methods and accordingly the performance metrics were analyzed.

4.1 Performance analysis of network formation time

A significant amount of time is said to be consumed during the formation of agriculture WSN. This is because of the reason that according to the number of samples or sensors, agriculture field of interest, soil moisture and soil temperature, the network formation time differs. The network formation time is mathematically stated as given below.

$$NF_{time} = \sum_{i=1}^{n} S_i * Time\,[y_t] \tag{17}$$

From the above equation (17), the network formation time 'NF_{time}' is evolved based on the sample agriculture nodes involved in the simulation process 'S_i' and the time consumed in optimal topology formation '$Time\,[y_t]$'. It is measured in terms of milliseconds (ms). Table 1 lists the performance evaluation results of network formation time using the proposed PDLA-SFH and existing methods, Digital Twins [1] and AGPSO [2] by substituting the values in equation (17).

Table 1
Performance evaluation of network formation time using BNVO-PR, OVEAP [1], RoadSegNet [2]

Samples	Network formation time (ms)		
	PDLA-SFH	Digital Twins	AGPSO
50	1.75	2.1	2.75
100	2.15	2.45	3.15
150	2.35	3	3.85
200	2.85	3.35	4.25
250	3	3.85	4.85
300	3.35	4.15	5.35
350	3.55	4.55	6
400	4	5	6.55
450	4.15	5.85	7.35
500	4.85	7	8.35

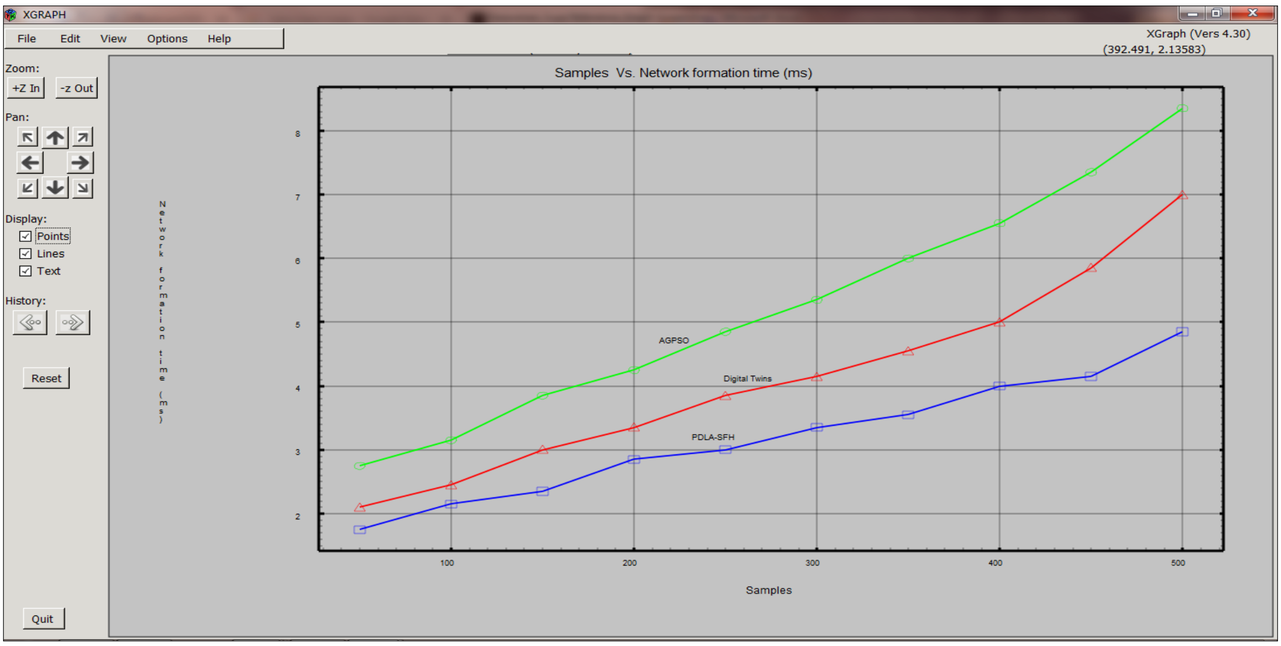

Fig. 4. Network formation time versus sensor samples

Figure 4 illustrates the network formation time or the time involved in agriculture field monitoring for sensor network formation with respect to distinct numbers of sensor samples in process. From the above figure it is inferred that increasing the sensor samples results in the increase of point of interest and therefore increasing the overall localization process also. However, with simulations performed for 50 sensor samples, the time for agriculture field monitoring for sensor network formation, i.e., the time consumed in performing the overall localization process was found to be 1.75ms using PDLA-SFH method, 2.1ms using [1] and 2.75ms using [2]. From this result it is inferred that the network formation time using PDLA-SFH method was found to be comparatively lesser upon comparison with [1] and [2]. The reason behind the minimization of network formation time using PDLA-SFH method was owing to the application of Game Theory Partial Derivative Regression Coefficient-based Topology algorithm. By applying this algorithm, initially, the agricultural network initialization was made by utilizing the potential game theory that specifically concentrated on the transmission power. Following which, a Partial Derivative Regression model was applied to the game theory results for the corresponding according to volumetric water readings and temperature readings. With this the network formation time using PDLA-SFH method was said to be reduced by 21% compared to [1] and 382% compared to [2].

4.2 Performance analysis of network formation error rate

The second major performance metric that has a great influence on agriculture sensor network formation is the error rate. The error rate is said to occur because of the difference in the volumetric water readings according to the depth measurement and also due to the difference in the temperature reading. The error rate is mathematically formulated as given below.

$$NF_{error} = \sum_{i=1}^{n} \frac{S_{\epsilon_{ik} > Pos_{ik}}}{S_i} \tag{18}$$

From the above equation (18), the network formation error rate 'NF_{error}' is measured by taking into consideration the sample agriculture nodes involved in the simulation process 'S_i' and the samples with approximation error greater than the position error '$S_{\epsilon_{ik} > Pos_{ik}}$' respectively. It is measured in terms of percentage (%). Table 2 lists the performance evaluation results of network formation error rate using the proposed PDLA-SFH and existing methods, Digital Twins [1] and AGPSO [2] by substituting the values in equation (18).

Table 2
Performance evaluation of network formation error rate using BNVO-PR, OVEAP [1], RoadSegNet [2]

Samples	**Network formation error rate (%)**		
	PDLA-SFH	Digital Twins	AGPSO
50	4	6	10
100	4.35	6.85	10.25
150	5	7.35	10.75
200	6.16	8	10.85
250	7	9.25	11
300	8.35	10	11.55
350	9	10.55	13
400	9.85	11.25	13.35
450	10	12	14
500	10.55	13.15	14.85

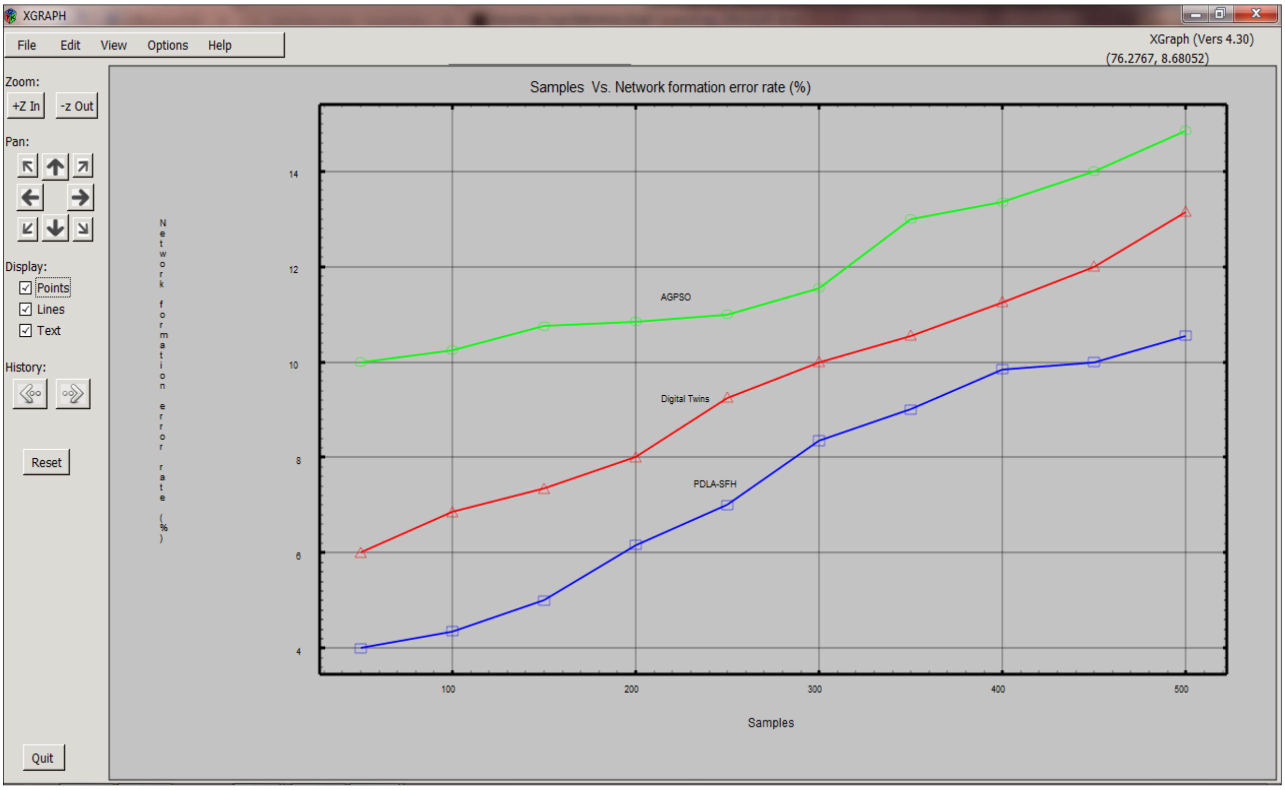

Fig. 5. Network formation error rate versus sensor samples

Figure 5 given above illustrates the graphical representation of network formation error rate with respect to 500 distinct sensor samples obtained at different time intervals with file containing locations of each of the 42 monitoring locations. Also, from the above figure an increasing trend is observed with 500 different samples conducted for an average of 10 simulation runs. Nevertheless, with simulations performed using 50 samples 2 wrong position updates or estimations were made when applied with PDLA-SFH, 3 and 5 wrong position updates were made when applied with [1] and [2]. With this the network formation error rate using the three methods were found to be 4%, 6% and 10% respectively. From this result the network formation error rate using PDLA-SFH was found to be comparatively better than [1] and [2]. The reason behind the minimization of error rate using PDLA-SFH was due to the of Laurent Singularity-based Hop Size Distance validation algorithm. By applying this algorithm two distinct errors were evolved by taking into consideration the approximation and position error for distinct regular sensor node and anchor sensed nodes. Following which, on the basis of the resultant error values, an approximation function was applied to arrive at the hop distance. This in turn resulted in the minimization of agricultural sensor network formation with minimal error using PDLA-SFH method by 23% compared to [1] and 39% compared to [2] respectively.

4.3 Performance analysis of network formation accuracy

The third influencing factor in agriculture sensor network formation is the accuracy with which the configuration is said to be established. To be more specific, based on the validation results, the network formation accuracy is ensured. The network formation accuracy is measured as given below.

$$NF_{acc} = \sum_{i=1}^{n} \frac{S_{\epsilon_{ik} \geq Pos_{ik}}}{S_i} \tag{19}$$

From the above equation (19), the network formation accuracy 'NF_{acc}' is measured based on the sample sensors involved in the simulation process 'S_i' and the percentage of error in distance validation '$S_{\epsilon_{ik} \geq Pos_{ik}}$'. It is measured in terms of percentage (%). Table 3 lists the performance evaluation results of network formation accuracy using the proposed PDLA-SFH and existing methods, Digital Twins [1] and AGPSO [2] by substituting the values in equation (19).

Table 3
Performance evaluation of network formation accuracy using BNVO-PR, OVEAP [1], RoadSegNet [2]

Samples	Network formation accuracy (%)		
	PDLA-SFH	Digital Twins	AGPSO
50	96	94	92
100	95.35	93.15	91.35
150	95	93	91
200	94.25	92.55	90.25
250	94.15	92	89.15
300	93.85	91.55	88.35
350	93.65	91.05	88
400	92.85	90	86.35
450	92.35	88.15	86
500	92	87	85.45

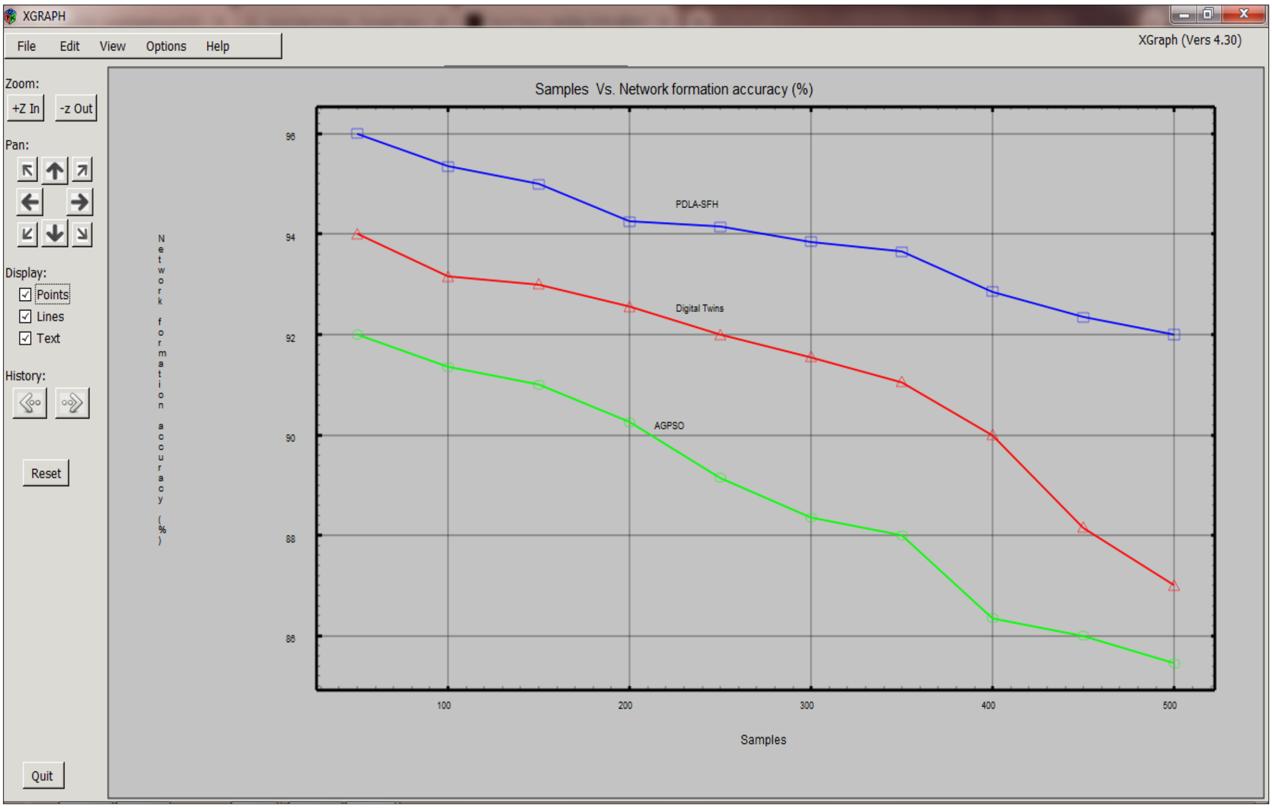

Fig. 6. Network formation accuracies versus sensor sample

Figure 6 given above shows the network formation accuracy involved in the process of agriculture sensor network formation. From the above figure, the network formation accuracy is found to be in the decreasing trend with the increase in the sensor samples ranging between 50 and 500. This is because two different classes of volumetric water and temperature readings with five distinct depths were involved in the simulation process and also positioned randomly. For example, with simulations performed using 50 sensor samples, 48 sensor samples were correctly positioned as it is and therefore ensuring intelligent and robust network formation using PDLA-SFH method whereas only 47 and 46 sensor samples were positioned correctly with the aid of [1] and [2], respectively. As a result, the overall network formation accuracy performed for 10 simulation runs using the three methods were observed to be 96%, 94% and 92% respectively. This result showed accuracy improvement using PDLA-SFH method upon comparison to [1] and [2]. The reason behind the improvement was due to the application of Stochastic Feedforward Hyperbolic-based Position Estimation algorithm. By applying this algorithm, initially, Stochastic Feedforward network was modeled initially in the first input layer. Following which between anchor sensed and regular sensing nodes both distance and position estimates were made via distance estimation. Finally, location information was arrived at that in turn improved the network formation accuracy using PDLA-SFH method by 3% compared to [1] and 6% compared to [2] respectively.

4.4 Performance analysis of network formation complexity

Finally, network formation complexity for sensor network formation is measured. Complexity here refers to the storage space occupied while performing the entire process. The network formation complexity is measured as given below.

$$NF_{comp} = \sum_{i=1}^{n} S_i * Mem\ [y_t] \tag{20}$$

From the above equation (20), the network formation complexity 'NF_{comp}' is measured on the basis of the sample sensors involved 'S_i' and the memory consumed in the overall network formation process '$Mem\ [y_t]$'. It is measured in terms of kilobytes (KB). Table 4 lists the performance evaluation results of network formation complexity using the proposed PDLA-SFH and existing methods, Digital Twins [1] and AGPSO [2] by substituting the values in equation (20).

Table 4
Performance evaluation of network formation complexity using BNVO-PR, OVEAP [1], RoadSegNet [2]

Samples	**Network formation complexity (KB)**		
	PDLA-SFH	Digital Twins	AGPSO
50	52.5	77.5	92.5
100	65.35	85.35	105.35
150	71.25	95.25	115.25
200	80	105.35	135.15
250	95.35	115.55	150.35
300	100.15	135.35	165.35
350	115.85	150.55	185.25
400	135.35	185.25	215.55
450	150	205.35	245.35
500	175.85	235.15	260.35

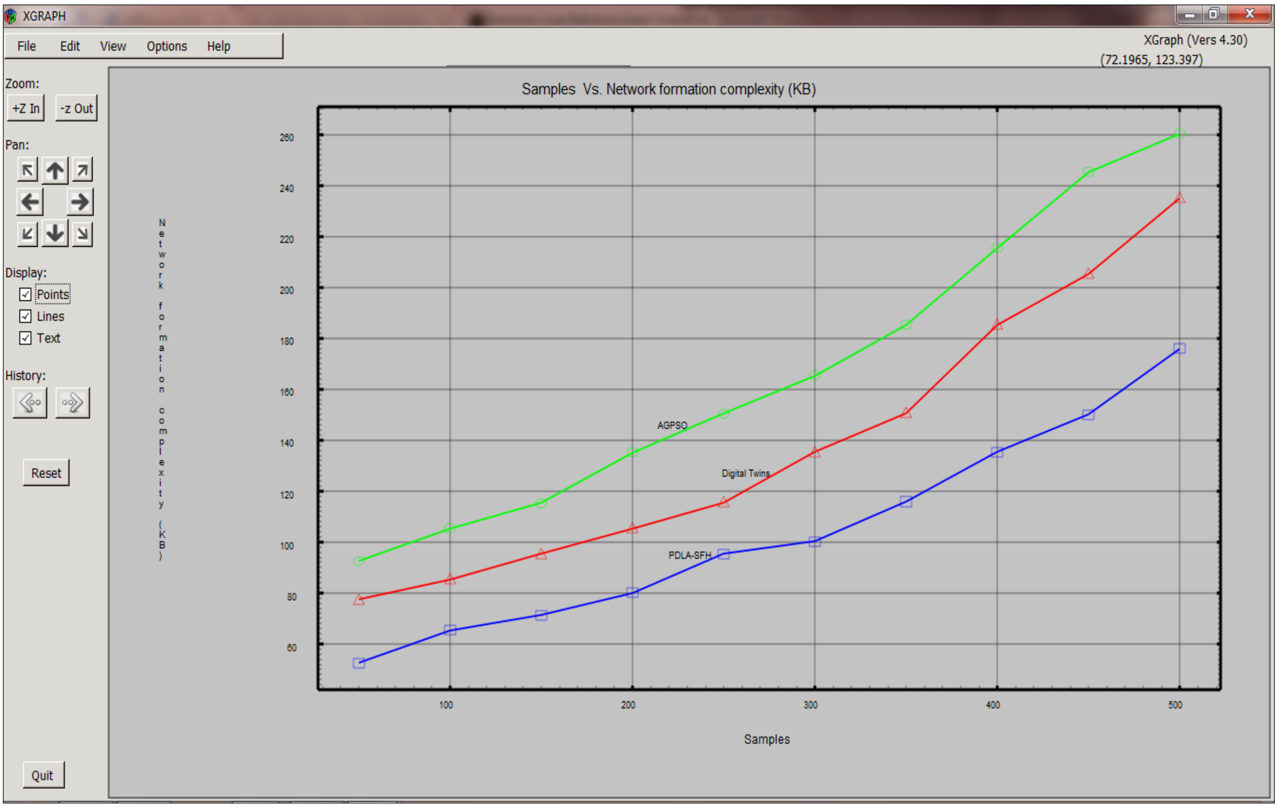

Fig. 7. Network formation complexities versus sensor sample

Figure 7 given above illustrates the graphical representation of network formation complexity versus 500 distinct sensor samples. From the above figure it is inferred that increasing the sensor samples results in the increase in continuous monitoring, measuring and analyzing of different physical features and occurrences for sensor network formation. This in turn would increase the network formation overhead for distance validation and position estimation, therefore increase in the overall sensor network traffic management also. However, simulations performed with 50 sensor samples using the proposed PDLA-SFH method was observed to be 52.5KB, 77.5KB using [1] and 92.5KB using [2]. The reason behind the minimum complexity incurred using PDLA-SFH method was owing to the application of Stochastic Feedforward Hyperbolic-based Position Estimation. By applying this model, two distinct functions were applied for arriving at the results of distance and position estimates. Here, the distance estimate was made based on the coordinate of anchor sensed node and coordinate of regular sensing node. By combing these two functions, matrix representation was made separately, therefore guaranteeing intelligent network formation for agricultural field. This in turn reduced the network formation complexity using PDLA-SFH method by 25% compared to [1] and 38% compared to [2] respectively.

5. Conclusion

The evolution of machine learning based sensor network formation intelligent routing for precision agriculture in wireless network results in considerable evolution or development in novel techniques to known issues. However, the network formation for agriculture farmland application frequently necessitates machine learning solutions that can be accomplished by cautious arrangement of neural network model architecture. The Partial Derivative Laurent Approximation and Stochastic Feedforward Hyperbolic (PDLA-SFH) presented in this paper is one possible solution for intelligent and robust Agriculture Sensor Network Formation. The aim of our work was to achieve successful farm management via sensor network formation using a Partial Derivative Laurent Approximation that is suitable for inference and deployment in wireless networks. Having this in mind, we designed and implemented PDLA-SFH with sensor network formation for crop management ensuring intelligent and robust design for quality control. The main contribution of proposed method is the novel solution that is computationally efficient due to application of Game Theory Partial Derivative Regression Coefficient-based Topology construction. Also, by validating hop distance by means of two distinct approximation and position error, the overall network formation error was said to be reduced significantly. Finally, accuracy was also focused using Stochastic Feedforward Hyperbolic-based Position Estimation algorithm. The performance analysis of proposed PDLA-SFH method-based Agriculture Sensor Network Formation is compared with existing Digital Twins [1] and AGPSO [2] using various metrics that are 22% of network formation time, 31% of network formation complexity, 5% of network formation accuracy and 32% of network formation error rate with numbers of sensor samples.

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